Social Distance and Geographical Proximity in the Social Networking Service Sphere:Social Network Analysis between Facebook Co-likers1

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Social Distance and Geographical Proximity in the Social Networking Service Sphere: Social Network Analysis between Facebook Co-likers[1]

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1. Introduction

In this article, I would like to examine the relation of geographical and social distance between co-likers on a Facebook® page[2] that is targeting regional information. This trial can be said to be an analysis of online social networking. At present, social networking services, SNS, involve huge numbers of users. SNS have the potential to produce a social phenomenon regardless of where one actually lives. Facebook, the world's largest SNS, has approximately 1.1 billion worldwide users, according to a May 2013 survey, though the users are distributed disproportionally in the world. In Japan today, about 19.6 million users subscribe to Facebook. Additionally, more than 70 local Japanese governments are actually running Facebook pages for the purpose of receiving local people's direct input and reacting to their needs effectively. Principally, the local governments are publishing useful regional information and community events to the local people. In this article, I will focus on the Saitama City Facebook page and its co-likers for the postings. *Co-likers* is defined as the fan users who send favorable feedback to the target posting and also to other co-likers. I propose some research questions regarding inter-co-liker relationships, in which geographic proximity should be examined to determine whether it is correlated to co-likers' social distance. To answer these questions, the place of residence was extracted from each co-liker's Facebook page. The co-likers' data was collected and arranged, and a social network analysis (SNA) was implemented using NodeXL, UCINET, and NetView for examining the relation between the geographical proximity and the social distance of

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the co-likers.

Generally speaking, in a real-life community, neighbors have a lot of communication thanks to their physical closeness. Local people have built their shared culture, tradition, and dialect, etc. over a long time, especially in a rather small community. They have shared a common knowledge and lifestyle based on where they live. We cannot ignore the commonality among local people from several points of view. Could such local tendencies be applied to an online local community? How does the social distance of an online SNS community matter as compared to the geographical distance among SNS users? In this article, I have examined the above questions in an attempt to understand the inter-regional relationships of co-likers using social network analysis.

2. Computer-Mediated Communication

To conduct this research, the computer-mediated communication (CMC) paradigm should be mentioned first. Much research into how people use computer-mediated communication has concentrated on how individual users interface with their computers, how two people interact online, or how small groups function online. More than a few researchers have pointed out that virtual communities are completely different from real ones. However, many researchers have been emphasizing the significant role of CMC. CMC is playing a supplementary role for real communication, not preventing people from communicating face to face in daily life.

Since online communities were born in the Internet sphere, many researchers have been discussing the light and dark sides of CMC. As Steven Jones points out (Jones, 1995), "connection to the Internet does not inherently make a community, nor does it lead to any necessary exchanges of information, meaning and sense making at all". Cyber utopians and cyber dystopians debate frequently. Cyber utopians Hampton and Wellman argued in a paper on local community in a wired suburb near Toronto, Canada:

The Internet especially supports increased contact with weaker ties, and in comparison to non-wired residents of the same suburb, more neighbors are known and chatted with, and they are more geographically dispersed around the suburb. Not only did the Internet support neighboring, it also facilitated discussion and mobilization around local issues. (Hampton and Wellman, 2003)

However, to the cyber dystopians, Internet communities do not enhance face-to-face communication. One of the surveys based on time-diary data, Nie and Hillygus examined the impact of Internet use on face-to-face interaction. They concluded that Internet use at home has a strong negative impact on time spent with friends and families as well as on social activities except time spent at work (Nie and Hillygus, 2002).

While it is true that there are more than a few people who think that Internet use prevents real activity in a local community, Hampton and Wellman claimed that the Internet does not override social ties of other types, but is merely an additional tool that people use to connect with each other (Hampton and Wellman, 2003). As they said, the advantage of CMC is twofold: one is that CMC is asynchronous, and the other is that it allows communication from one to many. People can read and write messages when they want, which is helpful because, in modern life, they are pressed for time. With CMC, they can arrange communication when they have time available, which makes them feel comfortable and improves their weak ties. In addition, CMC's broadcasting capability also brings portability of information to people, which can help them form social ties that provide chances to meet with people in the real world.

3. Facebook

The first recognizable online social-network website, SixDegrees.com, was launched in 1997. It attracted many users, but it failed as a business in 2000, probably because the market was not yet ripe for the concept. In 2002, Friendster was launched to compete with Match.com in the USA. Unlike Match.com and similar dating sites that were focused on facilitating the introduction of strangers, Friendster exploited the idea that friends of friends would be a better pool from which to draw romantic partners. But Friendster limited friends' relations by four degrees of separation (friends of friends of friends of friends), and this limitation prevented Friendster users from extending their online communication to real-world communication. Finally, Friendster disappeared. After that, Myspace was launched in 2003. From the beginning, it placed a strong emphasis on attracting fans of indie rock bands, and it allowed users to develop connections to the bands and to other fans of the bands. It resembles Facebook in that it also creates fan pages on which Facebook users can access and join it. However, Myspace was soon overshadowed by Facebook.

The online social network, Facebook, began at Harvard in 2004. Twenty-five years earlier, it had started from a paper-based students' directory; the students depended on it for social life on campus. Then, the book was reborn into the online version by Harvard sophomore Mark Zuckerberg; it became so popular that it quickly spread to other institutions. Originally Facebook users were only members of a college community. Within a year, membership opened up to high schools as well, and later to geographically specified communities and corporate networks. In June 2008, Facebook surpassed MySpace in total worldwide users to become the largest online social network. In May 2013, Facebook had more than 1.11 billion worldwide users, including 19.6 million users in Japan, which means that one out of six Japanese people are Facebook users. Although, in Japan, *Mixi* is the largest SNS site, the number of Facebook users is increasing. It has been said that the many Facebook users think that their online life is pretty relevant to their real-world social networks (Christakis, 2009).

The number of Facebook users was counted at 1.1 billion in June 2012, which corresponds to about 15% of entire world's population. In fact, by way of Facebook, the world's biggest online social networking service, regardless of their real distance, people around the world are now communicating with each other. Considering research on Facebook pages, there are more than a few interpersonal network analyses on Twitter. Contrary to Twitter's feasibility for social network analysis, Facebook presents some difficulties in getting some data because of security reasons for Facebook compliance. It is not possible for any other people to access data about friends except for their own personal networks. Evidently we can see any Facebook page according to the security options selected and can see partly who are the friends of whom, but we cannot extract the friends data on other people's Facebook pages automatically with computer software. The data we can extract are co-likers and co-comments on any other person's Facebook page, from which there are some attributes that can be gleaned, like a person's name, sex, language, etc. I use NodeXL[3] to acquire data for self-assigned dates.

4. Social Network Analysis

Social Network Analysis, SNA, is an analytical method that focuses on the structure and patterns of relationships between and among people, organizations, states, and other entities. SNA is useful for determining structural relationships among and between online communities. To compare that much CMC research requires concentrating on how the technical attributes of different communication media might affect what can be conveyed via each medium. SNA focuses on relationships, in other words, the ties between the nodes in the network, and thinks that the relationships determine the social structure of network members and even the social behavior of each member. Regarding the online social network, an electronic tie combined with an organizational tie is sufficient to allow the flow of information between people who may never have met face to face. Connectivity among previously unacquainted people is a well-established finding in the CMC research literature. Online SNA would be a promising method that not only makes headway in CMC research, but also finds some characteristics essential to online communication from various points of view. In this article, I tried to verify the relation between social distance and graphical distance in the online community, as on the Internet, loosely connected networks provide people with considerable room to act autonomously and to switch between relationships.

5. Research Questions

People living in cities where the economic and cultural situations correlate strongly tend to connect more strongly than do those in cities not having any particular relationships. Is geographical distance not a concern for socio-geographical relationships? I would like to examine this question as it relates to the Facebook community. Research questions addressed include:

A. Does offline geography still matter in online social networks, for the purpose of this article, Facebook?
B. Who in which region talks to whom in which region?
C. Is there some geographical tendency between co-likers?

From these academic results, it is meaningful to examine the data from the Facebook network, one of the very popular Internet communities in actual society as well as an incarnated form of CMC. Do people living in cities that have similar lifestyles and cultures also have strong relationships in the digital sphere? I would like to analyze this on Facebook group sites, although it is a very limited space. For example, it would be a bit of an exaggeration, but since the Middle Ages, cities that mutually imported and exported each other's products have been strongly connected regardless of their geographical distance. Have such relations changed in today's society in which online communities are introduced on the Internet?

6. Related Work

• The Blog Network in America

An analysis of U.S. weblogs has been done to examine the interpersonal networks and social connections among U.S. cities. Using NITLE[4] census data, about 120,000 blogs were examined. With custom-made modified programs, locations (U.S. cities) were extracted from the blogs. Research questions included: To what degree are the hypertextual expressions of blog authors related to the geographical locations from which they blog, where the centers of opinion leaders are, where their clusters of opinion congregations are, and how they are identified. Comparing geographical information with mutual links on the blog, the locations were ranked by popularity, in-links, and out-links, then cluster analysis was conducted. Thirty significant clusters and dyads were found to answer the research questions described above. Some interesting findings were shown in the analysis: bloggers do not always communicate according to geographical closeness. They are bound psychologically; they share a common lifestyle. For example, one cluster shows the strongest connection between Manhattan, San Francisco, and some extremely urbanized large cities and, in contrast, a cluster among suburbs in Chicago and Oklahoma, and yet another cluster with a weak connection between Cleveland, San Diego, and Princeton. From the analysis, bloggers who live in cities whose ways of life are similar are likely to communicate well in digital space, not necessarily related to where they live. Apparently, research was limited because of a lack of blog and link data from many small cities; however, it predicts the possibility of using links among weblogs to measure sociogeographical relationships and suggests some interesting national patterns of discursive clustering.

• Measuring Social Distance

How do we measure social distance between people in a community? Regardless of whether the community is real or virtual, what factors contribute to people's social distance, besides geography? Hampton and Wellman hypothesized that the use of CMC, with the concomitant increase in the frequency of communications and the numbers of others with whom we communicate, will decrease the importance of proximity in neighborhoods. This is a question of space. Space here is not only geographical, but also social; in other words, the distance between two people is measured by social ties rather than by geographical distance. Thanks to CMC's asynchronous nature, we have collapsed the barrier of time zone distances between people around the globe. Such a shift to social space has influenced people's communities and relationships. Thanks to the Internet, the world is shrinking socially; I would like to examine how it is shrinking by using the Facebook groups community.

• Geography of Twitter Networks

Takhteyev and her colleagues examined Twitter networks around the world to prove how weak asymmetric ties affect regional clusters. They used an available Twitter data sample to show a substantial share of ties that lie within the same metropolitan region. They examined the co-relation between the regions that the ties belong to from four perspectives: geographical distance, national borders, language difference, and airline flights. Consequently, Twitter connections were affected by airline flights, highlighting the importance of not just looking at geographical distances. They concluded that the frequency of airline connections can be a proxy for the more general connectedness, and the number of flights appeared to be the best predicator of non-local weak ties, emphasizing the importance of structural constraints on ties rather than on sample physical distances.

7. Target Data

I focused on an interesting Facebook community to draw their geographical relation. *Saitama City(さいたま市)* was selected as the community from which I gathered "co-likes" data with NodeXL software, the Excel plug-in network analysis tool. Saitama City is situated south of Saitama, whose neighbor on the north is Tokyo. Saitama City is the capital of Saitama Prefecture; its population is about 1.23 million. Saitama is one of Tokyo's bedroom communities; many commuters who live in Saitama work in Tokyo.

Saitama City was created by the Saitama City Office in 2012. The office provides information on city events and other regionally useful information. Image 1 shows the Saitama City Facebook page. Actually there are 802 co-likers. The site is actively commented upon by the city office day by day. Every time an article is posted, many members comment immediately.

Figure 1. Saitama City Facebook page (screenshot as of August 25, 2013) [5]

I selected the data of the Saitama City Facebook page from June 3 to 25, 2013. During that period, 61 articles were posted. The postings were varied, such as the following:

- リサイクル品展示販売会（Exhibition and sale of recycled products)
- ホタル観賞と音楽の夕べ 2013（Evening of fireflies and a music recital)
- 夏休み特別企画「親子で行く！大宮総合車両センター探検隊」(Summer special event — Adventures with the family at the JR East Omiya Sogo Sharyo Center)
- （トラブル注意報）高齢者を狙った健康食品の送りつけ商法が増えています
  (Alert) Be careful not to be cheated by food sales tactics targeted at the elderly claiming health benefits.
- 今年初めてセミの鳴き声を聞いたら教えてください！
  (Tell us when you hear the first buzzing of cicadas this summer!)

In total, there were actually about 2,300 fan users and 802 active users. The page is always submitted by the Saitama City office, not by fan users.

8. Methodology

For SNA, I used NodeXL, a free, open-source template for Microsoft® Excel® that makes it easy to explore network graphs. In NodeXL, by searching Facebook fan pages and groups, the list of co-likers for each posting can be generated in the Excel format. (See Figure 2 below.)

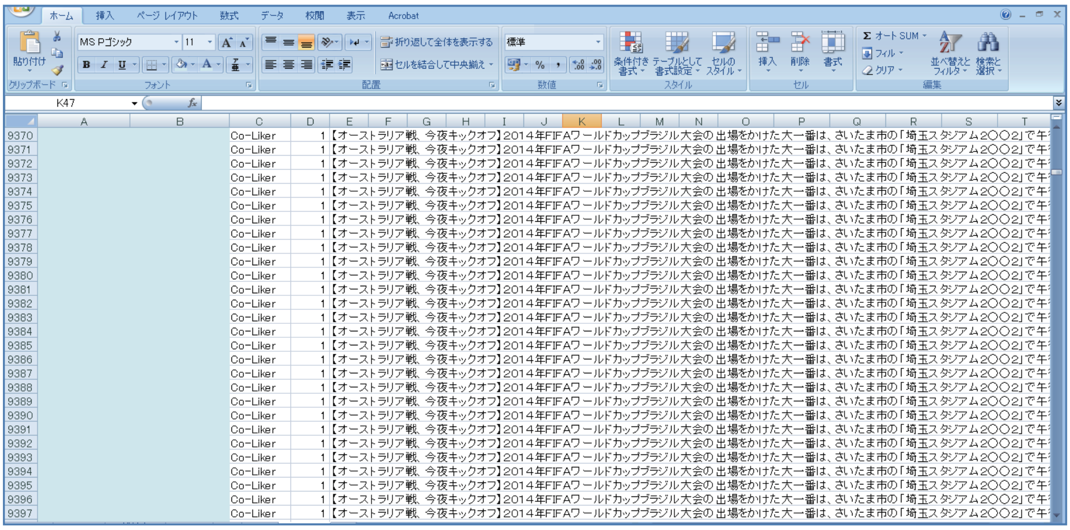


Figure 2. NodeXL output of co-likers list

For security, columns A and B are hidden by a rectangle. Column A shows co-likers who sent a “favorite” comment to a posting by a user in column B. Column Q indicates the content of the posting, in this screenshot, it is written: “The Japan vs. Australia trial match for the 2014 FIFA World Cup in Brazil will be held at Saitama Stadium in Saitama City.” For this post, more than a few co-likers responded.

UCINET[6] was used for data analysis. After arranging the data for social network analysis, the data was inputted to UCINET for getting some network measures and implementing Quadratic Assignment Procedure (QAP) (Figure 3).

- NodeXL Output

  As shown in Figure 2, NodeXL outputs some attributes about posters and co-likers, for example, their name, sex, locale, and the URL of their Facebook site. Normally, NodeXL should indicate hometowns; however, I was not able to get this information. Alternatively, the hometowns of the posters and their co-likers were extracted by hand from their Facebook page using their URL. The posters and their co-likers were assigned as nodes in the social network analysis. Below, Table 1 shows information of the nodes and the ties of the target article. For each site, there are nodes of a prefecture, e.g., Tokyo, and ties of two prefectures, e.g., Osaka and Okinawa. The nodes have multiple ties with the alter nodes[7]. Table 1 shows the number of co-likers and co-liker pairs in the target data.

Table 1. Co-likers information

	No. of co-likers	No. of co-liker pairs
Total	822	96,203
With hometown	416 (411)	21,247 (19,707)

- Add the current living place to the nodes.

  From Facebook pages, information about the current living place was collected manually and added to each node.

- Arrange the data.

  Some Facebook pages do not include place information; in other words, the page owners are not intending to publish their living place. The dyads without living places were deleted, and non-individual nodes, such as companies or organizations, were also deleted because this research does not consider the relations between non-individuals.

- Determine the distance between prefectures in adjacency matrices.

  After arranging the data, only prefecture information was used for data analysis. The ties list generated by NodeXL was changed into a ties list in which each tie has a pair of prefecture names, for example, 'hokkaido-tokyo,' and so on. The ties list was transformed into an adjacency matrix shown in Figure 4. At the same time, an adjacency matrix of geodetic distance between two prefectures was prepared for the following analysis, shown in Figure 5. This matrix is composed of the Japanese prefectures that are in the adjacency matrix generated by the posters and the co-likers of the target Facebook page. This means that not all prefectures are in the matrix.

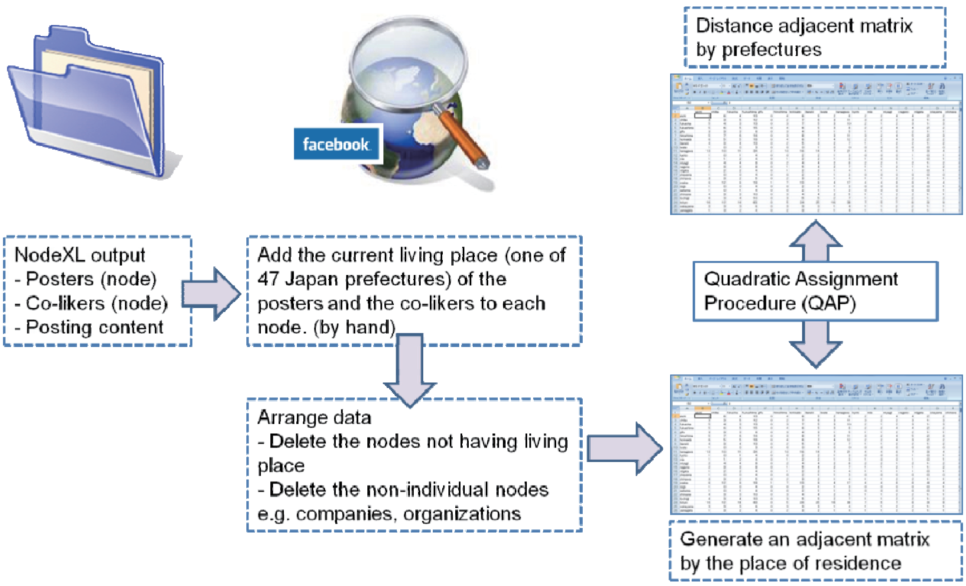
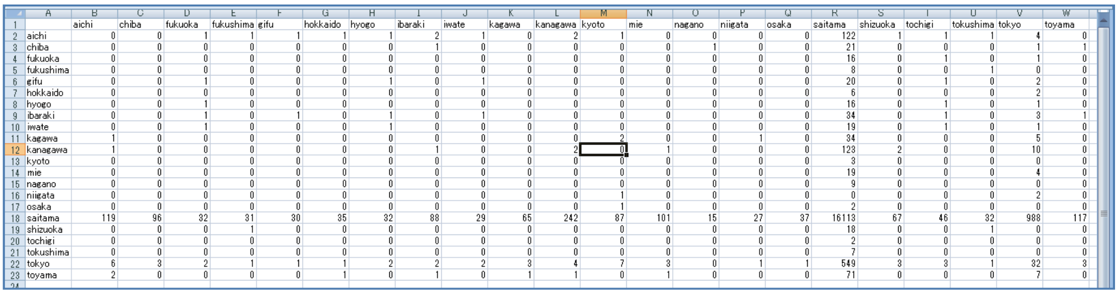
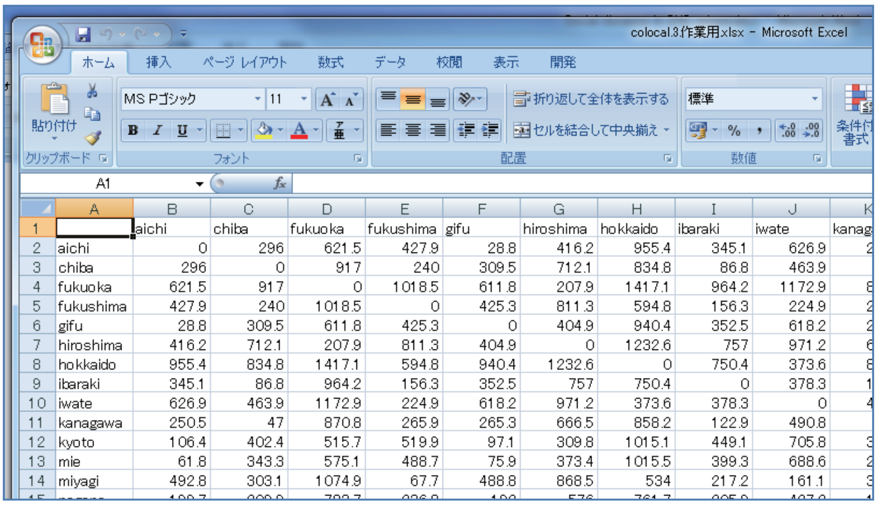


Figure 3. Workflow of the data analysis



	aichi	chiba	fukuoka	fukushima	gifu	hokkaido	hyogo	ibaraki	iwate	kagawa	kanagawa	kyoto	mie	nagano	niigata	osaka	saitama	shizuoka	tochigi	tokushima	tokyo	toyama
aichi	0	0	1	1	1	1	1	2	1	0	2	1	0	0	0	0	122	1	1	1	4	0
chiba	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	21	0	0	0	1	1
fukuoka	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	1	0	1	0
fukushima	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	1	0	0
gifu	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	20	0	1	0	2	0
hokkaido	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	2	0
hyogo	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	1	0	1	0
ibaraki	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	34	0	1	0	3	1
iwate	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	19	0	1	0	1	0
kagawa	1	0	0	0	0	0	0	0	0	0	0	2	0	0	1	0	34	0	0	0	5	0
kanagawa	1	0	0	0	0	0	0	1	0	0	2	0	1	0	0	0	123	2	0	0	10	0
kyoto	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
mie	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	4	0
nagano	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0
niigata	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0
osaka	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0
saitama	119	96	32	31	30	35	32	88	29	65	242	87	101	15	27	37	16113	67	46	32	988	117
shizuoka	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	1	0	0
tochigi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
tokushima	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0
tokyo	6	3	2	1	1	1	2	2	2	3	4	7	3	0	1	1	549	3	3	1	32	3
toyama	2	0	0	0	0	1	0	1	0	1	1	0	1	0	0	0	71	0	0	0	7	0

Figure 4. Fragment of an adjacency matrix by posters and co-likers



	aichi	chiba	fukuoka	fukushima	gifu	hiroshima	hokkaido	ibaraki	iwate
aichi	0	296	621.5	427.9	28.8	416.2	955.4	345.1	626.9
chiba	296	0	917	240	309.5	712.1	834.8	86.8	463.9
fukuoka	621.5	917	0	1018.5	611.8	207.9	1417.1	964.2	1172.9
fukushima	427.9	240	1018.5	0	425.3	811.3	594.8	156.3	224.9
gifu	28.8	309.5	611.8	425.3	0	404.9	940.4	352.5	618.2
hiroshima	416.2	712.1	207.9	811.3	404.9	0	1232.6	757	971.2
hokkaido	955.4	834.8	1417.1	594.8	940.4	1232.6	0	750.4	373.6
ibaraki	345.1	86.8	964.2	156.3	352.5	757	750.4	0	378.3
iwate	626.9	463.9	1172.9	224.9	618.2	971.2	373.6	378.3	0
kanagawa	250.5	47	870.8	265.9	265.3	666.5	858.2	122.9	490.8
kyoto	106.4	402.4	515.7	519.9	97.1	309.8	1015.1	449.1	705.8
mie	61.8	343.3	575.1	488.7	75.9	373.4	1015.5	399.3	688.6
miyagi	492.8	303.1	1074.9	67.7	488.8	868.5	534	217.2	161.1

Figure 5. Fragment of an adjacency matrix of the physical distance between Japanese prefectures

9. Network Analysis Findings

After screening the data without a place and transforming the user data into prefecture names data, finally 21,037 ties were left with 22 prefecture nodes. Using the data, some SNA have been conducted with the methods described below. The targeted network can be said to be an ego network in which Saitama Prefecture is the center because the Facebook page is owned by the Saitama City Office, and many fan users living in Saitama City are members. It is normal for Saitama City fan users to subscribe to their own city to obtain useful and appealing information.

In the analysis, as 47 Japan prefectures were implemented as nodes, Saitama City data was included in Saitama Prefecture's node with the other cities in Saitama Prefecture. Anyway, among the cities in Saitama Prefecture, Saitama City occupied the dominant position as compared with others.[8] However, some fan users from other cities also subscribe to the page. In the analysis, I took the targeted network as Saitama City's ego network, in which Saitama is the ego and the other 21 prefectures are alters, because this network expresses how Saitama City attracts the other prefecture fan users as well as inhabitants in Saitama proper. Though formally the network would be a complete type, the network is logically an ego-centered network whose ego is Saitama. The targeted network can be said to be a complete network if it transmits various regional information everywhere in Japan.

The following analyses have been conducted: basic network measures, like out-degree, in-degree, and betweenness, then visualization of this ego-centered network with NetView,[9] and, finally, the quadratic assignment procedure (QAP) has been applied for observing the co-relation between the target data adjacency matrix and geodetic distance matrix to verify the research questions described in this article.

A) Basic Network Measures

Table 2 is an output by UCINET, where out-degree, in-degree, and betweenness are indicated for the 22 target prefectures.

Table 2. In-degree, out-degree, and betweenness of the Saitama ego network

		OutDeg	Indeg	Between
		--------	--------	--------
1	aichi	14	5	8.5
2	chiba	5	2	0.833
3	fukuoka	3	7	0
4	fukushima	2	4	0
5	gifu	6	4	0
6	hokkaido	2	4	0
7	hyogo	4	6	0
8	ibaraki	8	6	4.833
9	iwate	5	5	0
10	kagawa	5	3	0.583
11	kanagawa	7	5	0.583
12	kyoto	1	6	0.833
13	mie	2	4	0
14	nagano	1	2	0
15	niigata	2	3	0
16	osaka	2	2	0
17	saitama	22	21	225.5
18	shizuoka	3	4	0.5
19	tochigi	1	8	0
20	tokushima	1	5	0
21	tokyo	21	15	95.5
22	toyama	8	4	3.333

Table 3. Degrees and density as a completed network of Saitama City

Avg Degree	5.545
Density	0.264
Avg Distance	1.738
SD Distance	0.445

As expected, Saitama is the maximum out- and in-degree and, in particular, has enormous betweenness. It can be logical that Saitama is taken as the ego in the targeted network. Tokyo and Aichi are following in the three measures cited above. Both are among the biggest cities in Japan, and the detailed data show that many people living in Tokyo came from Saitama and vice versa. It is not surprising that people living in Tokyo are sufficiently interested in Saitama City to subscribe to its Facebook page, as there are strong connections between Saitama and Tokyo geographically and psychologically. Regarding Aichi, we cannot clearly determine the reason, but Aichi is also one of the largest cities in Japan, situated almost in the middle of Honshu. Many people in Aichi have a relatively strong interest in a Kanto metropolitan city. Particularly, Saitama City has two strong football teams that are very popular in Japan, and the popularity of the teams would attract people from a neighboring metropolitan area to the Kanto region cities. Figure 6 shows a visualization of the Saitama City Facebook fan page network.

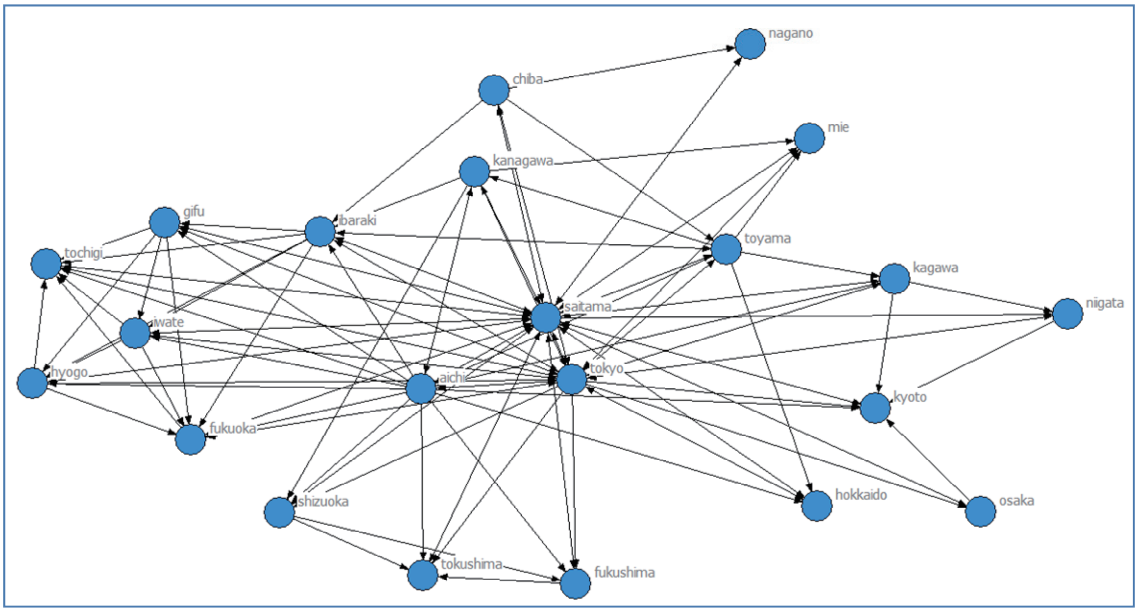


Figure 6. Visualization of the Saitama City Facebook Fan Page Network

The next screenshot of NetView shows a slightly modified design of the same network highlighting Saitama as the ego and the others as the alter. The size and the colors of the nodes vary according to their degree (Figure 7).

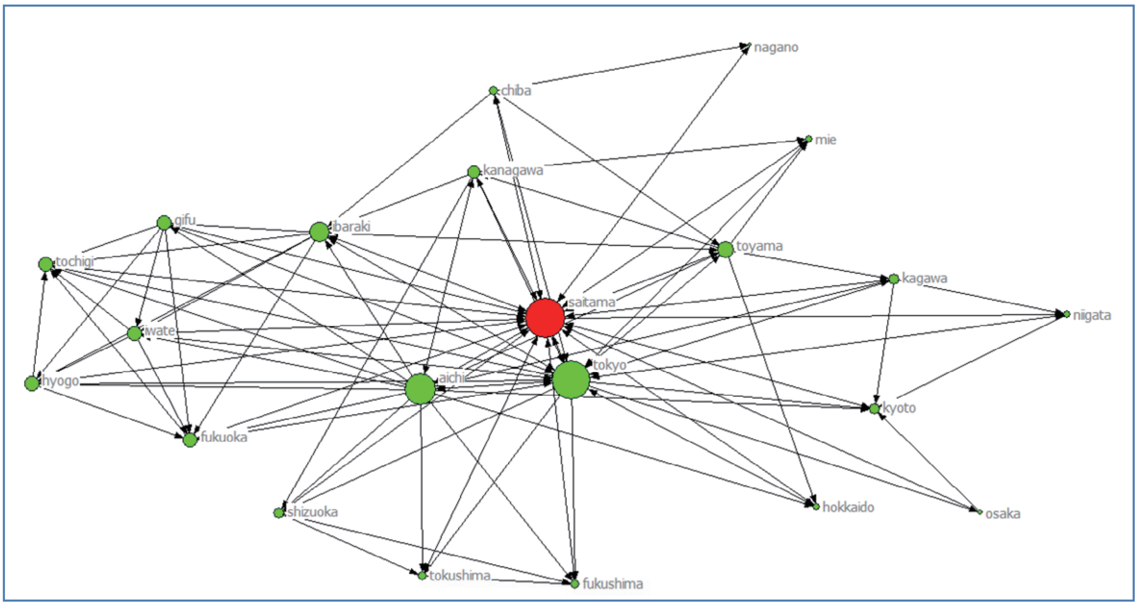


Figure 7. A more highlighted version of the Saitama City Network

From Figure 7, some prefectures with strong connections around Saitama exist: e.g., Tokyo, Aichi, Kanagawa, Ibaraki, and Toyama. In Figure 7, the place of the node represents how strong a connection a pair of ties has. The stronger a pair of ties is connected, the closer the ties are in the network space.

Taking geographical distance from Saitama into consideration, as Figure 8 shows, some prefectures are in the network around Saitama, mainly including the Kanto district.

Figure 8. Map of Japan and some prefectures around Saitama

In Figure 8, besides Saitama, there are 10 prefectures[10] in common with the Saitama City Network. In spite of 50% commonality, we must be careful of drawing an easy conclusion as the prefectures neighboring Saitama in the map were randomly chosen by the author's simple judgment. In addition, 4[11] out of 7 Kanto district prefectures[12] in the map as shown in the network connect relatively strongly to Saitama. It appears that people neighboring Saitama have a greater tendency to subscribe to the Saitama City Facebook page than do other Japanese districts. Could it show that offline geography still matters regarding who in which region talks to whom in which region and that there is some geographical tendency between co-likers? Advancing from such an instinctive observation, I tried to apply QAP to this article's research questions.

B) Quadratic Assignment Procedure (QAP)

In addition to descriptive network measures, I analyzed the effects of physical geodetic distance using correlation with the quadratic assignment procedure, QAP. QAP makes it possible to test the correlation between graphs while compensating for the auto-correlation inherent in network graphs and in a popular approach for graph comparison. In this article, QAP has been done using UCINET 6.463 (Borgatti 2002).

In advance, I prepared a geodetic distance matrix as shown in Figure 5. The physical distance between two prefectures means the geodetic distance between the capital cities of each prefecture. To obtain this data, I referred to *the Geospatial Information Authority of Japan* website.[13] Then I collected and arranged the pairs of two prefectures into an adjacency matrix using UCINET. The physical distance matrix was rearranged into a new one in which each cell is divided by 1, the inverse number of the original value. In other words, the more the co-likers in the two prefecture are connected, the less the distance. In Figure 5, the diagonal elements are 0; then the elements were replaced with 1. Figure 9 shows a modified inverse matrix of the physical distance matrix of Figure 5.

	aichi	chiba	fukuoka	fukushima	gifu	hokkaido	hyogo	ibaraki	iwate	kagawa
aichi	1	0.003378	0.001609	0.002337	0.034722	0.001047	0.006006	0.002898	0.001595	0.003595
chiba	0.003378	1	0.001091	0.004167	0.003231	0.001198	0.002167	0.011521	0.002156	0.001746
fukuoka	0.001609	0.001091	1	0.000982	0.001635	0.000706	0.002195	0.001037	0.000853	0.0029
fukushima	0.002337	0.004167	0.000982	1	0.002351	0.001681	0.001713	0.006398	0.004446	0.001447
gifu	0.034722	0.003231	0.001635	0.002351	1	0.001063	0.006231	0.002837	0.001618	0.003686
hokkaido	0.001047	0.001198	0.000706	0.001681	0.001063	1	0.000933	0.001333	0.002677	0.000864
hyogo	0.006006	0.002167	0.002195	0.001713	0.006231	0.000933	1	0.001956	0.001302	0.008953
ibaraki	0.002898	0.011521	0.001037	0.006398	0.002837	0.001333	0.001956	1	0.002643	0.001605
iwate	0.001595	0.002156	0.000853	0.004446	0.001618	0.002677	0.001302	0.002643	1	0.001152
kagawa	0.003595	0.001746	0.0029	0.001447	0.003686	0.000864	0.008953	0.001605	0.001152	1
kanagawa	0.003992	0.021277	0.001148	0.003761	0.003769	0.001165	0.002408	0.008137	0.002037	0.0019
kyoto	0.009398	0.002485	0.001939	0.001923	0.010299	0.000985	0.015649	0.002227	0.001417	0.005741
mie	0.016181	0.002913	0.001739	0.002046	0.013175	0.000985	0.00823	0.002504	0.001452	0.00434
nagano	0.005008	0.004764	0.001276	0.004223	0.005208	0.001313	0.002875	0.004857	0.002341	0.0022
niigata	0.002804	0.00366	0.001096	0.007794	0.002887	0.00165	0.002017	0.004662	0.003671	0.001674
osaka	0.007246	0.002317	0.00206	0.001787	0.007424	0.000945	0.032362	0.00207	0.001337	0.007097
saitama	0.003849	0.019531	0.001135	0.004496	0.003702	0.001229	0.002346	0.011148	0.002237	0.001859
shizuoka	0.007326	0.005784	0.001336	0.002777	0.006325	0.001071	0.003397	0.004158	0.001727	0.002475
tochigi	0.003229	0.009191	0.001083	0.007077	0.00319	0.001366	0.002111	0.017762	0.002735	0.00171
tokushima	0.004029	0.001863	0.002586	0.001489	0.004054	0.000862	0.011111	0.001688	0.001166	0.017699
tokyo	0.00386	0.024876	0.001136	0.004186	0.003686	0.001203	0.002352	0.01007	0.002156	0.001863
toyama	0.005872	0.003465	0.001414	0.003207	0.006609	0.001265	0.003469	0.00342	0.002082	0.002575

	kanagawa	kyoto	mie	nagano	niigata	osaka	saitama	shizuoka	tochigi	tokushima	tokyo	toyama
aichi	0.003992	0.009398	0.016181	0.005008	0.002804	0.007246	0.003849	0.007326	0.003229	0.004029	0.00386	0.005872
chiba	0.021277	0.002485	0.002913	0.004764	0.00366	0.002317	0.019531	0.005784	0.009191	0.001863	0.024876	0.003465
fukuoka	0.001148	0.001939	0.001739	0.001276	0.001096	0.00206	0.001135	0.001336	0.001083	0.002586	0.001136	0.001414
fukushima	0.003761	0.001923	0.002046	0.004223	0.007794	0.001787	0.004496	0.002777	0.007077	0.001489	0.004186	0.003207
gifu	0.003769	0.010299	0.013175	0.005208	0.002887	0.007424	0.003702	0.006325	0.00319	0.004054	0.003686	0.006609
hokkaido	0.001165	0.000985	0.000985	0.001313	0.00165	0.000945	0.001229	0.001071	0.001366	0.000862	0.001203	0.001265
hyogo	0.002408	0.015649	0.00823	0.002875	0.002017	0.032362	0.002346	0.003397	0.002111	0.011111	0.002352	0.003469
ibaraki	0.008137	0.002227	0.002504	0.004857	0.004662	0.00207	0.011148	0.004158	0.017762	0.001688	0.01007	0.00342
iwate	0.002037	0.001417	0.001452	0.002341	0.003671	0.001337	0.002237	0.001727	0.002735	0.001166	0.002156	0.002082
kagawa	0.0019	0.005741	0.00434	0.0022	0.001674	0.007097	0.001859	0.002475	0.00171	0.017699	0.001863	0.002575
kanagawa	1	0.002802	0.003372	0.005333	0.003598	0.002595	0.022026	0.007937	0.007943	0.002041	0.036765	0.00386
kyoto	0.002802	1	0.013158	0.00352	0.002307	0.023256	0.002737	0.004168	0.002435	0.006553	0.002737	0.004394
mie	0.003372	0.013158	1	0.003826	0.002391	0.011025	0.003207	0.00576	0.002723	0.00516	0.003239	0.004403
nagano	0.005333	0.00352	0.003826	1	0.006341	0.003078	0.006301	0.005356	0.006553	0.00229	0.005787	0.011521
niigata	0.003598	0.002307	0.002391	0.006341	1	0.002102	0.004279	0.003034	0.005995	0.001707	0.003957	0.00478
osaka	0.002595	0.023256	0.011025	0.003078	0.002102	1	0.002516	0.003789	0.002238	0.008929	0.002526	0.003698
saitama	0.022026	0.002737	0.003207	0.006301	0.004279	0.002516	1	0.006631	0.012285	0.001979	0.052632	0.004203
shizuoka	0.007937	0.004168	0.00576	0.005356	0.003034	0.003789	0.006631	1	0.004494	0.002737	0.007003	0.004585
tochigi	0.007943	0.002435	0.002723	0.006553	0.005995	0.002238	0.012285	0.004494	1	0.001793	0.010121	0.004177
tokushima	0.002041	0.006553	0.00516	0.00229	0.001707	0.008929	0.001979	0.002737	0.001793	1	0.00199	0.002643
tokyo	0.036765	0.002737	0.003239	0.005787	0.003957	0.002526	0.052632	0.007003	0.010121	0.00199	1	0.00401
toyama	0.00386	0.004394	0.004403	0.011521	0.00478	0.003698	0.004203	0.004585	0.004177	0.002643	0.00401	1

Figure 9. Modified inverse matrix of the physical distance matrix

QAP has been done using the physical distance matrix and the co-likers living place matrix as shown in Figure 4. QAP correlations[14] and P values are shown in Table 4.

Table 4. QAP correlations

	co-likers connection	physical distance
co-likers connection	1.000	0.509 $p = 0.0004$
physical distance	0.509 $p = 0.0004$	1.000

Observing the output of the QAP, it is clear that there is a rather strong correlation between co-likers and physical distance, as the correlation coefficient is 0.509. It can be said that the proximity of co-likers is strongly connected. The P value also proved the null hypothesis testing to be rejected with a 0.1% significance level. In this analysis, the null hypothesis is that there is no relation between co-likers and physical proximity. However, the results show a rather strong statistical relation between co-likers and their physical proximity.

10. Conclusion and Future Works

In this article, three research questions were proposed concerning geographical distance between fan users on the Saitama City Facebook site. The ties between co-likers were focused on through social network analysis. To conclude this article, I would like to come back to the three research questions:

A. Does offline geography still matter in online social networks, for the purpose of this article, Facebook?

The QAP results in the previous chapter indicate that offline geography or physical proximity matters in a fan users network of the Saitama City Facebook page.

B. Who in which region talks to whom in which region?

Table 5 shows a complete adjacency matrix for this question. There are 22 prefectures, including Saitama itself, figured in Table 5.

Table 5. Complete adjacency matrix of the prefectures of co-likers

	aichi	chiba	fukuoka	fukushima	gifu	hokkaido	hyogo	ibaraki	iwate	kagawa	kanagawa
aichi	0	0	1	1	1	1	1	2	1	0	2
chiba	0	0	0	0	0	0	0	1	0	0	0
fukuoka	0	0	0	0	0	0	0	0	0	0	0
fukushima	0	0	0	0	0	0	0	0	0	0	0
gifu	0	0	1	0	0	0	1	0	1	0	0
hokkaido	0	0	0	0	0	0	0	0	0	0	0
hyogo	0	0	1	0	0	0	0	0	0	0	0
ibaraki	0	0	1	0	1	0	1	0	1	0	0
iwate	0	0	1	0	0	0	1	0	0	0	0
kagawa	1	0	0	0	0	0	0	0	0	0	0
kanagawa	1	0	0	0	0	0	0	1	0	0	2
kyoto	0	0	0	0	0	0	0	0	0	0	0
mie	0	0	0	0	0	0	0	0	0	0	0
nagano	0	0	0	0	0	0	0	0	0	0	0
niigata	0	0	0	0	0	0	0	0	0	0	0
osaka	0	0	0	0	0	0	0	0	0	0	0
saitama	119	96	32	31	30	35	32	88	29	65	242
shizuoka	0	0	0	1	0	0	0	0	0	0	0
tochigi	0	0	0	0	0	0	0	0	0	0	0
tokushima	0	0	0	0	0	0	0	0	0	0	0
tokyo	6	3	2	1	1	1	2	2	2	3	4
toyama	2	0	0	0	0	1	0	1	0	1	1

	kyoto	mie	nagano	niigata	osaka	saitama	shizuoka	tochigi	tokushima	tokyo	toyama
aichi	1	0	0	0	0	122	1	1	1	4	0
chiba	0	0	1	0	0	21	0	0	0	1	1
fukuoka	0	0	0	0	0	16	0	1	0	1	0
fukushima	0	0	0	0	0	8	0	0	1	0	0
gifu	0	0	0	0	0	20	0	1	0	2	0
hokkaido	0	0	0	0	0	6	0	0	0	2	0
hyogo	0	0	0	0	0	16	0	1	0	1	0
ibaraki	0	0	0	0	0	34	0	1	0	3	1
iwate	0	0	0	0	0	19	0	1	0	1	0
kagawa	2	0	0	1	0	34	0	0	0	5	0
kanagawa	0	1	0	0	0	123	2	0	0	10	0
kyoto	0	0	0	0	0	3	0	0	0	0	0
mie	0	0	0	0	0	19	0	0	0	4	0
nagano	0	0	0	0	0	9	0	0	0	0	0
niigata	1	0	0	0	0	0	0	0	0	2	0
osaka	1	0	0	0	0	2	0	0	0	0	0
saitama	87	101	15	27	37	16113	67	46	32	988	117
shizuoka	0	0	0	0	0	18	0	0	1	0	0
tochigi	0	0	0	0	0	2	0	0	0	0	0
tokushima	0	0	0	0	0	7	0	0	0	0	0
tokyo	7	3	0	1	1	549	3	3	1	32	3
toyama	0	1	0	0	0	71	0	0	0	7	0

C. Is there some geographical tendency between co-likers?

As the QAP results indicate, there is some geographical tendency between co-likers. We do not forget that the result is just a fragment of data from the Saitama City network, which is only a tiny part of the Facebook pages worldwide. However, the result of this article is expected to give a hint for social network analysis in an actual SNS sphere.

Online social network analysis is increasingly needed in this current digital age. Analysts want to know how online communities affect face-to-face communications, how relations off-line affect relations online, and how SNA describes social structure. In addition, I would like to conduct SNA on other Facebook pages to draw more clear SNA-specific findings as well as geographical distance; and I would like to clarify the social structure shaped by SNS users that have fan pages in common.

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[1] Co-likers means the fan users who send favorable feedback to the target posting and also to other co-likers.

[2] https://www.facebook.com/

[3] The Social Media Research Foundation, http://nodexl.codeplex.com/

[4] The National Institute for Technology in Liberal Education, http://www.nitle.org/

[5] https://www.Facebook.com/city.saitama

[6] Analytic Technologies, https://sites.google.com/site/ucinetsoftware/home

[7] Here 'alter nodes' means all the nodes but the target node .

[8] Actually, there are co-likers' residences in 24 other cities of Saitama Prefecture.

[9] NetView is the visualization tool with UCINET.

[10] Aichi, Chiba, Gifu, Ibaraki, Kanagawa, Nagano, Shizuoka, Tochigi, Tokyo, Toyama

[11] Ibaraki, Kanagawa, Tochigi, Tokyo

[12] Chiba, Gunma, Ibaraki, Kanagawa, Tochigi, Tokyo, Yamanashi

[13] 国土地理院 , http://www.gsi.go.jp/KOKUJYOHO/kenchokan.html

[14] Pearson Correlation

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La Proximité Géographique et la Distance Sociale du Service Réseau Social Sphère: Analyse Réseau Social parmi les “Co-Aimers” de “Facebook”

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Dans cet article, je voudrais vérifier la relation entre la proximité géographique et la distance sociale parmi “Co-Aimers” sur une page de “Facebook” qui publie des infos régionales. Cet essai se veut une analyse du réseau social en ligne en rapport avec Computer Mediated Communication (CMC). Je mettrai donc mon sujet sur la page de Facebook de la ville Saitama ainsi que les commentaires de ses Co-Aimers.

Je propose quelques questions sur des recherches au sujet de la relation inter-Co-Aimers dans lesquelles la proximité géographique doit être examinée si cela est en correspondance avec la distance sociale des Co-Aimers.

Pour répondre à ces questions, le lieu de la résidence est collecté sur la page de Facebook des Co-Aimers. Les données des Co-Aimers ont été collectées et arrangées. Ensuite L’analyse du réseau social (Social Network Analysis, SNA) fût réalisée avec NodeXL, UCINET et NetView pour examiner la relation entre la proximité géographique et la distance sociales des Co-Aimers.

En plus des mesures descriptives du réseau, j’ai analysé l’effet de la distance géographique physique en utilisant la corrélation avec le Procès Assignement Quadratique (Quadratic Assignment Procedure, QAP).

Les résultats du QAP indiquent qu’il y a des tendances géographiques parmi
Co-Aimers sur ladite page de Facebook.